Can Predictive Modeling Identify Head and Neck Oncology Patients at Risk for Readmission?

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Abstract
Objective. Unplanned readmission within 30 days is a contributor to health care costs in the United States. The use of predictive modeling during hospitalization to identify patients at risk for readmission offers a novel approach to quality improvement and cost reduction.

Study Design. Two-phase study including retrospective analysis of prospectively collected data followed by prospective longitudinal study.

Setting. Tertiary academic medical center.

Subjects and Methods. Prospectively collected data for patients undergoing surgical treatment for head and neck cancer from January 2013 to January 2015 were used to build predictive models for readmission within 30 days of discharge using logistic regression, classification and regression tree (CART) analysis, and random forests. One model (logistic regression) was then placed prospectively into the discharge workflow from March 2016 to May 2016 to determine the model’s ability to predict which patients would be readmitted within 30 days.

Results. In total, 174 admissions had descriptive data. Thirty-two were excluded due to incomplete data. Logistic regression, CART, and random forest predictive models were constructed using the remaining 142 admissions. When applied to 106 consecutive prospective head and neck oncology patients at the time of discharge, the logistic regression model predicted readmissions with a specificity of 94%, a sensitivity of 47%, a negative predictive value of 90%, and a positive predictive value of 62% (odds ratio, 14.9; 95% confidence interval, 4.02-55.45).

Conclusion. Prospectively collected head and neck cancer databases can be used to develop predictive models that can accurately predict which patients will be readmitted. This offers valuable support for quality improvement initiatives and readmission-related cost reduction in head and neck cancer care.

Keywords
readmission, 30-day readmission, quality improvement, predictive models, head and neck cancer

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Unplanned hospital readmissions within 30 days of discharge (30dUR) diminish quality of care and increase costs. Medicare estimates $17 billion is paid on the 20% of patients readmitted within 30 days of discharge.1 It is estimated that the US health care system spends more than $41 billion annually on 30dURs.2 Government initiatives aim to decrease readmissions through penalties imposed for rates exceeding determined standards.3,4 Much of this effort has focused on nonsurgical readmissions; however, the Centers for Medicare & Medicaid Services (CMS) has recently expanded their publicly reported outcome measures to include hip and knee replacements5 and are expected to include more surgical specialties in the future.

Reported rates of 30dUR after head and neck cancer surgery range from 7% to 16% with average cost greater than $35,000 per readmission.6-10 Previous series suggest prolonged length of stay, renal failure, and the presence of a G-tube to be independent predictors of readmission.6 While the health care industry has increasingly employed predictive modeling to stratify risk and enhance clinical decision making,11-14 to our knowledge, no group has published their experience developing models to predict 30dUR after head and neck cancer surgery.

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This study’s purpose is to (1) develop predictive models for 30dUR after head and neck cancer surgery using logistic regression, classification and regression tree (CART) analysis, and random forests using a prospectively collected head and neck cancer database and (2) prospectively implement one predictive model into the postoperative discharge workflow at a tertiary academic medical center to determine the model’s positive predictive value (PPV), negative predictive value (NPV), sensitivity, and specificity for predicting which patients are later readmitted within 30 days.

Materials and Methods

Patients

This study was approved by the University of Cincinnati Institutional Review Board. A prospectively collected head and neck cancer database was queried for inpatient surgical admissions. Inclusion criteria included biopsy-proven head and neck cancer of the oral cavity, oropharynx, hypopharynx, larynx, sinonasal cavity, or major salivary gland and admission to the University of Cincinnati Medical Center between July 2013 and January 2015 following an oncologic surgery by one of the authors. Exclusion criteria included an incomplete patient data set. Interventions were generally based upon the recommendations of the University of Cincinnati Multidisciplinary Tumor Board.

Methods and Statistical Analysis

Building predictive models using a head and neck cancer database. The data set was constructed through database query, chart review, interviews, and the prospectively collected comorbidities and perioperative data optimized to head and neck surgical oncology. Average adjusted gross income (AGI) by ZIP code was attained through the US Census Bureau and the 2010 National Census.

The dependent variable was hospital readmission within 30dUR. Independent variables were binary (Tables 1-3). Nonfistula wound complications included hematoma, seroma, and wound dehiscence.

Logistic regression, CART, and random forests were completed (using R Foundation for Statistical Computing, Vienna, Austria) to construct the predictive models for readmission. Using R, the data set was split randomly into a training set (63% of patients) and test set (37% of patients).

Logistic regression models were built using only the training set admissions. Correlations between predictor-independent variables were first assessed to avoid multicollinearity. The model was then created using training data by modeling all binary independent variables simultaneously and then iteratively removing the most nonsignificantly associated attributes, rebuilding the model, and repeating, until only significantly associated attributes remained. P values less than .05 were considered significant for all statistical tests. The resultant model was then employed to predict readmission within the test set to determine the model’s accuracy, positive predictive value, negative predictive value, sensitivity, specificity, odds ratio, and 95% confidence interval. Goodness of fit for the logistic regression models was assessed using classification tables and deviance residuals.

CART and random forests models were built using only the training set admissions and a threshold of 0.5 using the most predictive attributes in the logistic regression analysis. The resultant models were then employed to predict readmission within the test set to determine each model’s accuracy, positive predictive value, and sensitivity.

Predictive model’s prospective performance identifying readmitted patients. Using the logistic regression predictive model developed with the head and neck cancer database, a clinical decision support tool (CDS) was prospectively implemented into the discharge workflow for the head and neck oncology service for 3 consecutive months (March 2016 through May 2016) at a tertiary academic medical center. The team’s physician assistant flagged patients as “high risk” or “low risk” based on the CDS binary prediction at the time of discharge. 30dUR was tracked after the hospitalization for all patients discharged during this period to determine the model’s specificity and positive predictive value in preemptively identifying readmitted patients at their initial discharge.

### Table 1. Binary Independent Variables Used to Build Predictive Models: Preoperative Patient Attributes.

<table>
<thead>
<tr>
<th>Binary Independent Variables: Preoperative Attributes (n = 142) %</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Binary Independent Variables</strong></td>
</tr>
<tr>
<td>Age (&lt;50 years)</td>
</tr>
<tr>
<td>Age (50-65 years)</td>
</tr>
<tr>
<td>Age (≥65 years)</td>
</tr>
<tr>
<td>BMI &gt;30 kg/m²</td>
</tr>
<tr>
<td>BMI &lt;18.5 kg/m²</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
</tr>
<tr>
<td>Current tobacco use</td>
</tr>
<tr>
<td>Dyspnea at rest</td>
</tr>
<tr>
<td>Home oxygen requirement</td>
</tr>
<tr>
<td>Active COPD</td>
</tr>
<tr>
<td>History of MI</td>
</tr>
<tr>
<td>History of PCI</td>
</tr>
<tr>
<td>History of cardiac surgery</td>
</tr>
<tr>
<td>Previous chemotherapy</td>
</tr>
<tr>
<td>History of renal failure</td>
</tr>
<tr>
<td>Previous head and neck radiation therapy</td>
</tr>
<tr>
<td>ECOG patient status 2, 3, or 4</td>
</tr>
<tr>
<td>ZIP code average AGI</td>
</tr>
<tr>
<td>&lt;$30,000</td>
</tr>
<tr>
<td>Between $30,000 and $50,000</td>
</tr>
<tr>
<td>Between $50,000 and $90,000</td>
</tr>
<tr>
<td>&gt;$90,000</td>
</tr>
</tbody>
</table>

Abbreviations: AGI, adjusted gross income; BMI, body mass index; COPD, chronic obstructive pulmonary disease; ECOG, Eastern Cooperative Oncology Group; MI, myocardial infarction; PCI, Percutaneous Coronary Intervention. *ECOG patient status as published in the American Journal of Clinical Oncology.** Percentages are rate of occurrence in overall study population.
Results
Building Predictive Models

In total, 174 admissions met inclusion criteria. Thirty-two were excluded due to incomplete independent variable data sets. Predictive models were constructed using the remaining 142 admissions. The 30dUR was 19% for the total population (27 of 142), 19% in the training set (17 of 89), and 19% in the test set (10 of 53). Tables 1 to 3 include descriptive statistics of the independent variables for the population.

The logistic regression approach yielded a 4-variable model within the training set, including body mass index (BMI) \(<18.5 \text{ kg/m}^2\) \((P = .02449)\), fistula \((P = .00149)\), average ZIP code and AGI \(\$90,000\) \((P = .00217)\), and oral cavity primary site \((P = .00937)\). BMI \(<18.5 \text{ kg/m}^2\), fistula, and average zip code AGI \(\$90,000\) were positively correlated with readmission; oral cavity primary site was negatively correlated with readmission. In-sample performance within the training set yielded a 75% positive predictive value and 50% sensitivity. When applied to the test set, out-of-sample logistic regression performance yielded a 50% positive predictive value and a 40% sensitivity (Table 4).

In-sample random forest model was built as a classification problem with a minbucket of 3 within the training set yielding 98% accuracy, 100% positive predictive value, and 88% sensitivity. When applied to the test set, out-of-sample random forest performance yielded 100% positive predictive value and 30% sensitivity (Table 4).

Predictive Model’s Prospective Performance Identifying Readmitted Patients

The logistic regression model was employed as a simple CDS tool for 106 consecutive head and neck oncology service discharges at our tertiary academic medical center. The model demonstrated a 62% PPV with a specificity of 94%. It identified 47% of all readmitted patients at the time of discharge postoperatively, flagging 12% of the discharges as high risk (47% sensitivity). Table 4 is the output of a classification table for the logistic regression model in the prospective component of the study.

The overall readmission rate in this prospective sample was 16% (17 of 106 discharged patients). Reasons for readmission were hemorrhage (29%), pneumonia (24%), wound complication or infection (29%), cardiac arrest (6%), chest pain (6%), and epidural abscess (6%). Of readmitted patients, 41% had undergone free flap reconstruction, compared to 67% of all patients in the prospective sample. The model successfully predicted readmission secondary to 5 wound complications, 1 hemorrhage, 1 aspiration pneumonia, and 1 episode of chest pain.

Discussion

Health Care Value

The health care industry continues to explore alternative payment models that share risk across stakeholders to curtail
exorbitant delivery costs. Through capitation, bundled payments models, and other vertically integrated accountable care organization models, the industry is shifting slowly from a fee-for-service to a fee-for-value environment in which providers are incentivized to maximize quality while also limiting cost.3

30dUR after surgery adds avoidable cost through utilization of incremental hospital resources across health care services.1,2 In otolaryngology specifically, Dziegielewski et al6 estimate the mean “cost” per readmission to the health care ecosystem after head and neck cancer surgery to be $35,041.

Building Predictive Models

Current approaches to limiting readmission after specialty surgery include provider awareness of risk factors statistically associated with readmission,6,15 combined with “clinical intuition” based on long-range experience to cater to postoperative pathways. Wide variation of reported rates implies opportunity to improve processes that limit readmission.6-10

Predictive analytics aims to enhance expert intuition through iteratively synthesizing historical data to generate actionable models that predict future outcomes of interest, such as readmission. Predictive models in health care have been considered a form of CDS tools. To construct the CDS tool in this study, we “trained” models within a portion of the available historical data set (ie, the training set) to predict readmission. The resultant model’s performance was then tested in an untouched, randomly selected portion of the data set from which the model was not generated (ie, the test set). The model’s test set performance is thought to be a good projection of real-world performance. Thus, the goal of the present study was not to elucidate every independent variable correlated with readmission but rather to serve as a proof-of-concept study to assess the feasibility of using databases available at our center to build predictive models that accurately identify patients at higher risk for readmission as measured by the models’ sensitivity, specificity, PPV, NPV, and odds ratios.

In our test set simulation environment, the random forest model yielded the highest positive predictive value and odds ratio; however, it was not statistically significantly better performing than the other models (Table 4). Through flagging 5.6% of all discharges in the test set, the model identifies 30% of the readmissions. This model intentionally trades sensitivity to optimize PPV to limit expenditure of postdischarge resources on low-risk patients. In other words, by increasing the model’s “threshold” for designating an observation as high risk, it flags a smaller number of patients, hence accepting more false negatives to increase odds for true-positive outcomes.

Random forests is a machine-learning methodology that optimizes predictive power through compiling innumerable regression trees. Unlike the simple decision tree representation of CART results (Figure 1), random forests is too complex to simply conceptualize and more challenging to integrate into workflows because it would require an application interface to extract and manipulate data to arrive at the binary prediction. For this reason, we selected the logistic regression model initially to test prospectively for head and neck oncology service discharges over 3 months using a simple .csv CDS tool (Figure 2).

Predictive Model’s Prospective Performance Identifying Readmitted Patients

When placed into the discharge workflow at a tertiary care academic medical center, the logistic regression predictive model had 94% specificity and 64% PPV with an odds ratio of 14.5. It correctly identified 47% of the patients who were ultimately readmitted through flagging 12% of all discharges. This type of risk modeling may ultimately allow optimal application of greater resources to a narrow high-risk segment of discharged patients to limit readmission. For example, high-risk patients may receive increased frequency of clinic or telemedicine follow-up, home health care, or predischARGE counseling by social worker or case

Table 4. Comparison of the 3 Predictive Models Used in the Test Set Simulation and the Logistic Regression Model as It Performed Prospectively in the Discharge Workflow.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Sensitivity, %</th>
<th>Specificity, %</th>
<th>PPV, %</th>
<th>NPV, %</th>
<th>OR</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic regression (test set simulation environment)</td>
<td>40</td>
<td>91</td>
<td>50</td>
<td>87</td>
<td>6.5</td>
<td>1.27-33.20</td>
</tr>
<tr>
<td>Logistic regression (prospective use in workflow)</td>
<td>47</td>
<td>94</td>
<td>62</td>
<td>90</td>
<td>14.9</td>
<td>4.02-55.45</td>
</tr>
<tr>
<td>CART</td>
<td>40</td>
<td>92</td>
<td>50</td>
<td>87</td>
<td>6.5</td>
<td>1.27-33.20</td>
</tr>
<tr>
<td>Random forests</td>
<td>30</td>
<td>100</td>
<td>100</td>
<td>86</td>
<td>40.6</td>
<td>1.90-868.41</td>
</tr>
</tbody>
</table>

Abbreviations: CART, classification and regression tree; CI, confidence interval; NPV, negative predictive value; OR, odds ratio; PPV, positive predictive value.
managers, while low-risk patients may receive more standard, less intensive follow-up. The alternative of applying maximal resources to all discharged patients is time- and cost-prohibitive.

Interestingly, while some variables included in the logistic regression readmission model are anticipated (BMI <18.5 kg/m², presence of fistula), the high AGI ZIP code finding was unexpected. One could speculate that those in the higher AGI group have more resources at their disposal that allow access to the health care system and that the higher readmission rate is a function of fewer barriers to entry. It is not possible to determine from the present study if the same variables identified as “high-risk” flags would be predictive of readmission in a different hospital system or medical center, but this is an area of possible future study.

Limitations
Small sample size is a limitation of this study. The ability to aggregate large, accurate structured data sets continues to be challenging despite broad adoption of electronic medical records. While claims, laboratory, and microbiology data among others can be easily mined and structured directly from electronic medical records for modeling, high-integrity, granular clinical data around the surgical care cycle remain problematic to aggregate without manual effort. Our data set herein experienced significant attrition due to incomplete data capture that was not easily reconciled after the fact, hence limiting the ability to build the algorithm and test its performance out-of-sample. It follows that there is an opportunity to build large multi-institutional data sets to improve the performance of predictive modeling well beyond that of our small single-institution pilot study. Last, the models’ performance should also be compared to expert prediction of readmission at the time of discharge to demonstrate whether or not a tool is able to augment the intuition of experienced clinicians.

Conclusions
Predictive analytic models provide a substantive opportunity to identify patients at risk for readmission at the time of their initial discharge and hence are promising tools to drive quality improvement and cost reduction activities in health care. This study evaluates the application of modern data analytics techniques to predict readmission after head and neck cancer surgery first using simulation and then during in-field head and neck cancer discharge workflows. Future efforts will include optimizing the data collection process in a multi-institutional effort to expand the useable data set and further improve model performance, potentially through the use of segmentation and clustering techniques. More important, future efforts will aim to prospectively measure whether process improvement built upon readmission risk-profiling can ultimately decrease head and neck cancer readmission rates.

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Author Contributions
Amy M. Manning, study conception and design, acquisition of data, analysis and interpretation of data, drafting of manuscript; Keith A. Casper, study conception and design, acquisition of data, analysis and interpretation of data, final approval of manuscript; Kay St. Peter, acquisition of data, critical revision, final approval of manuscript; Keith M. Wilson, acquisition of data, critical revision, final approval of manuscript; Jonathan R. Mark, acquisition of data, critical revision, final approval of manuscript; Ryan M. Collar, study conception and design, acquisition of data, analysis and interpretation of data, drafting of manuscript, critical revision, final approval of manuscript.

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References


